The Human Toxicity Potential and a Strategy for Evaluating Model Performance in Life Cycle Impact Assessment

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Abstract. The Human Toxicity Potential (HTP) is a quantitative toxic equivalency potential (TEP) that has been introduced previously to express the potential harm of a unit of chemical released into the environment. HTP includes both inherent toxicity and generic source-to-dose relationships for pollutant emissions. Three issues associated with the use of HTP in Life Cycle Impact Assessment (LCIA) are evaluated here. First is the use of regional multimedia models to define source-to-dose relationships for the HTP. Second is uncertainty and variability in source-to-dose calculations. And third is model performance evaluation for TEP models. Using the HTP as a case study, we consider important sources of uncertainty/variability in the development of source-to-dose models – including parameter variability/uncertainty, model uncertainty, and decision rule uncertainty. Once sources of uncertainty are made explicit, a model performance evaluation is appropriate and useful and thus introduced. Model performance evaluation can illustrate the relative value of increasing model complexity, assembling more data, and/or providing a more explicit representation of uncertainty. This work reveals that an understanding of the uncertainty in TEPs as well as a model performance evaluation are needed to a) refine and target the assessment process and b) improve decision making.

Keywords: Human toxicity potential; InLCA; life cycle impact; model performance; model uncertainty; multimedia models; uncertainty; variability

1 Introduction

Life Cycle Assessment (LCA) requires quantitative measures of hazard as weighting factors for mass releases. But because the scope of an LCA does not allow for a full-scale risk assessment, Life Cycle Impact Assessment (LCIA) uses measures of hazard to compare the relative importance of pollutants within a defined impact category [1-5]. These impact categories include global warming, human health, ecosystem damage, ozone depletion, etc. Some LCIA categories are homogeneous, i.e., each pollutant has the same mechanism of action (global warming, ozone depletion). Other categories are necessarily heterogeneous, i.e., they contain pollutants that act according to different mechanisms of action (ecosystem stresses, human toxicity). Toxic equivalency potentials (TEPs) are a heterogeneous LCIA metrics that addresses potential impacts from releases of several chemicals into a number of environmental compart-

ments [2,5,6]. TEPs provide simplified representations of actual processes based on cardinal attributes. These attributes are developed using measured and/or estimated data in models that focus on factors judged to be crucial. The Human Toxicity Potential (HTP) is a quantitative TEP that was introduced by Guinée and Heijungs [1] to reflect the potential harm of a unit quantity of chemicals released into the environment by including both inherent toxicity and generic source-to-dose relationships.

In this paper, we consider three issues associated with the use of HTP in LCIA. First, we summarize the structure of the HTP and focus on its use of regional multimedia models to define source-to-dose relationships. Second, we explore the process for characterizing uncertainty and variability in the source-to-dose calculations. And third, we propose a model-performance evaluation for TEP models. The first two issues are addressed in the current literature, so only a summary evaluation is provided here. However, because a strategy for model performance evaluation has not yet been introduced to the LCIA process, we focus our findings and conclusions on this issue.

2 Human Toxicity Potential (HTP) as a Life Cycle Impact Metric

The Human Toxicity Potential (HTP) uses a margin-of-exposure ratio to express the potential for health impact from exposure to harmful agents, both carcinogens and non carcinogens [5,6]. HTP has been used to weigh emissions inventoried as part of an LCA and for the US Toxics Release Inventory (TRI) [5,6]. For example, it provides the cancer and non-cancer risk scores at www.scorecard.org/chemical-profiles/. The margin-of-exposure ratio is obtained by dividing an estimated cumulative dose by a toxicity benchmark, such as the unit risk dose for carcinogens and the reference concentration (RfC), or the reference dose (RfD) for non-carcinogens. RfC and RfD reflect a safe dose such as the allowable daily intake (ADI) that is used in Europe. The unit risk dose is the inverse of the cancer potency. For non-carcinogens, the toxicity benchmark is the RfD or, in some cases, the RfC. Because RfC and RfD are designed to provide a consistent margin of safety for exposure to non-cancer compounds, they provide a method for equalizing po-

tential impacts among chemical substances. The HTP exposure is expressed as the potential dose, which is calculated for a generic individual living in a 'unit world' model environment for a given release scenario. The margin-of-exposure ratio $H_{cn}(s_{cn} = 1)$ is calculated for each chemical c and each release compartment n (= air, surface water) based on a modeling of the potential dose following a unit release, that is for a source strength $s_{cn} = 1$ kg/day. The margin of exposure ratio for a given chemical and release scenario, H_{cn} is then normalized by the margin of exposure ratio for the reference chemical and reference release scenario (emissions to air) to yield the equivalency factor HTP_{cn}.

$$HTP_{cn} = \frac{H_{cn}(s_{cn} = 1)}{H_{refchem,air}(s_{refchem,air} = 1)} \qquad (1)$$

The overall HTP score of an emissions profile is obtained by multiplying the release of each chemical by the equivalency factor and then adding the resulting numbers. A different normalizing chemical is used for carcinogens and non-carcinogens.

$$HTP = \sum_{\substack{c \\ chemicals}} \left(\sum_{\substack{n\ release \\ compartments}} HTP_{cn} S_{cn} \right) \qquad (2)$$

Hertwich et al. [6] have developed cancer and non-cancer HTP values for air and surface-water emissions of 330 compounds.

Source-to-dose relationships for HTP are calculated using CalTOX, a set of spreadsheet models and data sheets that assess human exposures resulting from contaminants released to air, water, and the soil surface [7,8]. First issued in 1993 and updated in 1995, with continued enhancements underway, CalTOX consists of two component models – a multimedia transport and transformation model and a multipathway human exposure model that includes 23 exposure pathways. All
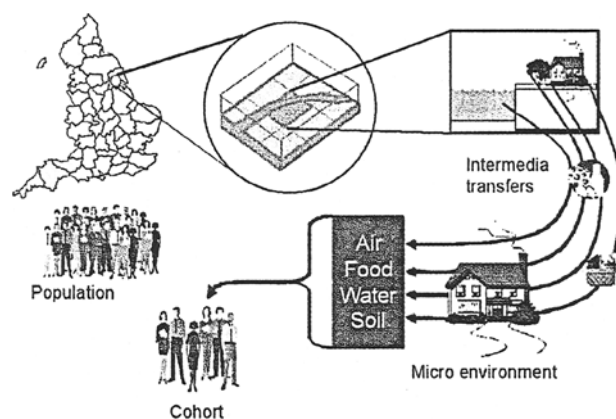
Fig. 1: A conceptual illustration of the source-to-dose relationship used in the HTP. A geographic region is represented by a 'unit landscape' to which a multimedia fate assessment is applied to link a continuous emission to air or water to steady-state environmental concentrations in air, water, soil, sediments and vegetation. Intermedia transfers are used to translate environmental concentrations into exposure media concentrations – in indoor air, tap water, food, house dust, etc. Intake and uptake for a cohort is defined based on their contact with the exposure media. The cohort is used as a proxy for the regional population.

inputs to CalTOX are represented as distributions, rather than as point estimates. This allows both sensitivity and uncertainty analyses to be directly incorporated into the model operation. CalTOX was the only U.S. model included in a 1994 international model comparison exercise organized by the Society of Environmental Toxicology and Chemistry [9]. **Fig. 1** illustrates the source-to-dose pathways included in CalTOX.

3 Uncertainty and Variability

Using the HTP as a case study, we note here important sources of uncertainty/variability in the development of source-to-dose relationships for TEPs. Quantifying source-to-dose relationships involves the use of large amounts of data coupled with the use of models. Because these data and models must be used to characterize individual behaviors, contaminant transport, human contact and uptake and dose among large and often heterogeneous populations, there is large variability and uncertainty associated with the resulting HTP values.

A framework for the analysis of uncertainty in human health risk assessment developed by Morgan and Henrion [10] and Finkel [11] has been applied by Hertwich et al. specifically to the HTP [12] and more generally to multimedia models used to establish source-to-dose relationships in TEPs [13]. This framework distinguishes among parameter uncertainty, model uncertainty, decision rule uncertainty, and natural variability in any of the parameters and calls for a separate treatment of the different types of uncertainty.

In evaluating parameter uncertainty and variability in the HTP process, Hertwich et al. [12] considered both uncertainty in chemical-specific input parameters as well as the variability in exposure factors and landscape parameters. They determined how the uncertainty and variability of these parameters impact estimates of potential dose calculation of 236 chemicals. The chemicals were grouped by dominant exposure route, and a Monte Carlo analysis was conducted for one representative chemical in each group. From this process, Hertwich et al. [12] found that variance in calculated dose for a specific chemical is typically one to two orders of magnitude. For comparison, the point estimates in potential dose for 236 chemicals span ten orders of magnitude. This demonstrates that the potential dose calculations for these chemicals offer a significant information gain relative to a more simple exposure index or the use of toxicity data alone. Most of the variance in the potential dose is due to chemical-specific input parameters such as the media-specific half-lives that can be highly uncertain. But exposure factors such as fish intake and the sources of drinking water can be important for chemicals whose dominant exposure is through ingestion routes. Landscape characteristics are generally of minor importance.

In an effort to better communicate the capabilities and limits of the HTP, Hertwich et al. [13] proposed for multimedia dose assessments an uncertainty analysis framework that addresses parameter uncertainty/variability as well as model uncertainty and decision-rule uncertainty. The framework was found helpful in organizing the analysis and identifying significant sources of uncertainty. Parameter uncertainty and variability are assessed through Monte Carlo analysis and can be made fairly comprehensive. But the analysis of model and decision rule uncertainties can as yet be only explor-

atory, because these two types of uncertainty are difficult to analyze quantitatively. The importance of model and decision uncertainty must be evaluated with systematic efforts to compare how different model choices and how implementation decisions change HTP scores. Hertwich et al. provide examples to illustrate these issues [13]. Model uncertainty is evaluated through two case studies, one using alternative formulations for calculating the vegetation concentrations and the other testing the steady state assumption for wet deposition. Decision rule uncertainty is explored through a comparison of the HTP values under open and closed system boundaries. This investigation reveals that steady state conditions for the removal of chemicals from the atmosphere are not always appropriate and can result in an underestimate of the potential dose for 25% of the 236 chemicals evaluated. The need remains for further analysis of model and decision-rule uncertainty in HTP calculations, specifically for how to structure models for metals and speciating organic chemicals, for the fate and effect of transformation products, and for the modeling of vegetation [13].

4 A Strategy for Model Performance Evaluation in HTP

Decisions supported by TEPs aim to avoid detrimental impacts from industrial activities on both human health and ecosystems. But as noted above, the process of calculating HTP and other TEP values includes inherent uncertainty and variability. Thus, in communicating with decision makers, LCIA practitioners must reveal and evaluate the uncertainty/variability of the TEP calculations. Often the issue on the mind of the decision maker is "How likely are we to be wrong and how much cost and delay is required to reduce the likelihood of a wrong decision?" Rarely can models alone answer this question. Thus, a key component of any proposed LCIA model framework is the support to first address features unique to each problem and to then define the level of confidence required to meet the performance objectives of an assessment. In this situation, model selection requires a model performance evaluation that can illustrate the relative value of increasing model complexity, assembling more data, and/or providing a more explicit representation of uncertainty [14-16].

4.1 Model validation and model evaluation

One approach for confronting TEP uncertainty is a systematic process for validating the models and data used to develop the TEPs. However, TEP models in general and the HTP models in particular belong to a class of models whose outcome cannot be truly validated [14,16,17,18]. Models that cannot be 'validated' can acquire user confidence through a rigorous process of model performance evaluation [14,16].

Hodges and Dewar [16] have defined the requirements for model validation and contrasted the attributes of and uses of models that can be truly validated from those that cannot. Models can only be validated for closed systems where inputs and outputs are all directly measurable and exhibit constancy (reproducibility) over time. Validity accrues when predictions made by the model are found true for variations in conditions not originally evaluated when the model was constructed. Some models cannot be validated, because these models are used to make predictions for outcomes that cannot be validated [16,18]. For ex-

ample, for a pollutant such as benzene, predicting the concentration attributable to a specific source category, (i.e refineries) is not a 'validatable' outcome. The concentration of benzene in the atmosphere in any region is not solely linked to the emissions from refineries, but could be attributable to several sources in the region and to sources transported into the region by long-range transport. Thus, we are dealing with an open system. As has been pointed out by Oreskes et al. [14] such open systems models, which are common in earth sciences, economics, and engineering as well as in the policy arena, cannot be fully verified or validated because the operative processes are always incomplete. Nevertheless, such models can be confirmed and can be used to put bounds on the likely range of outcomes [14,16,18]. In this sense the models can offer something of value to the policy-making process.

A model that cannot be validated does not prevent it from being useful; but only from being used to predict. Some common uses of unvalidatable models include [16]:
- To assist in decision making based on boundary condition analyses,
- As a means of illustrating an idea.
- As a tool to summarize data or provide an incentive for improving data quality.
- As a communication tool.
- As a teaching aid.
- To formulate hypotheses for subsequent testing.
- To provide a surrogate for reality, i.e., treat model predictions as if the model was valid.

4.2 Building model confidence

In the process of model performance evaluation, the greater the number and the diversity of confirming observations that can be made, the more probable it is that the conceptualization embodied in the model is not flawed. Confirming observations, however, do not demonstrate the veracity of a model or the hypthesis, they only support the probability that the model is valid or the hypothesis is not false. Although validity may not acrue, user confidence may increase.

Confidence is further enhanced if the user can easily inspect or verify the operation of the algorithm and data tansformations and determine whether the model is internally consistent and contains no obvious logical flaws or incorrect code implementation. Easy access to the raw data used as inputs, transformed data and the steps of data transformations used in the calculation, and the raw computer code for the algorithms underlying these data transformation will further enhance user confidence in the model. The availability of clear documentation for model structure, and the possibility of performing calibration against an external standard (test data sets) or an internal standard (parallel algorithms to perform the same calculation) all will increase user confidence in a model. The ability of a model to quantify the effects of variability or uncertainty in input parameters allows the user to gauge the source and magnitude of variability or uncertainty associated with the prediction.

5 Discussion and Conclusions

Multimedia fate models are now widely used for LCIA assessments. These models are difficult if not impossible to truly validate, but they have an established level of credibility. In

looking to the future use of these models, there is a trade-off among complexity, reliability, and confidence. As these models evolve and proliferate we must continue to evaluate their capabilities and limitations. There is a strong need to continue to the improve confidence placed in these models by decision makers. There is also the opportunity now to build more complex and spatially explicit multimedia models for LCIA. Are these two trends compatible? The increasing capability of personal computers makes possible ever more complex models and some decision makers equate complexity with confidence and credibility. But often the opposite is the case – complexity makes the models much more difficult to verify and evaluate and makes it particularly difficult to assess data limitations.

There is a need for a model evaluation process to support development of TEPs for LCIA based on multimedia exposure models. This process should illustrate the relative value of increasing model complexity, assembling more data, and/or providing a more explicit representation of uncertainty. As illustrated in **Fig. 2**, exposure models for LCIA can fall on a spectrum from complex and detailed models on the left to simple ranking models on the right.
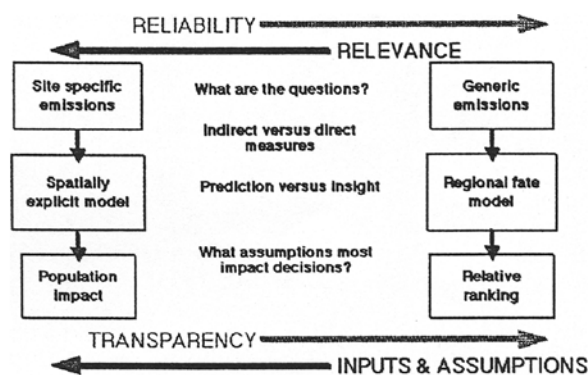

Fig. 2: An illustration of model development trade-offs that must be addressed in the model evaluation process for LCIA.

At the one extreme are the models that address site-specific emissions, treat transport and exposure using spatially explicit algorithms, and provide explicit calculation of population impact. At the other extreme are simple models that consider generic emissions, apply mass balance using a representative regional fate model, and often only provide a relative hazard ranking. We note that although models on the left end of this spectrum can provide the most relevant information for LCIA, they offer less reliability because of the large amounts of data required and the number of assumptions that must be made. Moreover, the models on the right are more transparent to the user, have less demand for inputs and data, but offer fewer degrees of freedom for characterizing impact. Deciding where to target an LCIA along this spectrum of model choices depends on the questions of the user. For example,

- If we control or reduce emissions of a given pollutant to the environment, how much reduction of total exposure (and related health effect) can be expected?
- How much of a change can be measured in my proximal indicator to provide evidence that the control measure is effective?
- How long is the lag time between a change in emissions and the measurable change in the environment or proximal indicator?

Given that these are questions most frequently in the mind of the decision makers and the public, it is important to formulate a modeling system to answer these questions. To achieve this requires an uncertainty/sensitivity analysis to reveal the power and limitations of LCIA models. Moreover, we must acknowledge that LCIA models are not validatable. Finally, we must recognize that confidence in LCIA models can accrue through an iterative process of evaluation.

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